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A MONTE-CARLO SIMULATION INVESTIGATING MEANS OF HUMAN-COMPUTER --ETC(U)
AUG 81 J S GREENSTEIN, M E REVESMAN N00014-81-K-0143
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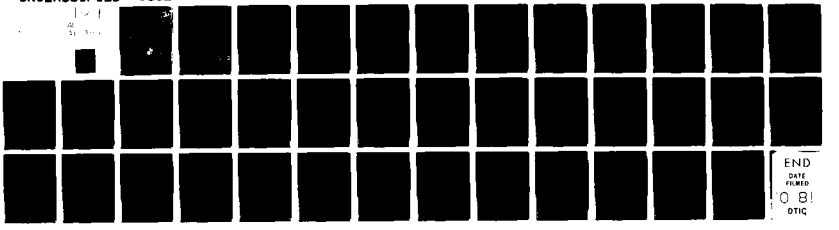

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A MONTE-CARLO SIMULATION INVESTIGATING MEANS OF HUMAN-COMPUTER COMMUNICATION FOR DYNAMIC TASK ALLOCATION

Joel S. Greenstein

Mark E. Revesman

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TECHNICAL REPORT

Prepared for
Engineering Psychology Programs, Office of Naval Research
ONR Contract Number N00014-81-K-0143
Work Unit Number SRO-101

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER CSIE-81-1 ✓	2. GOVT ACCESSION NO. AD-A103890	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) A MONTE-CARLO SIMULATION INVESTIGATING MEANS OF HUMAN-COMPUTER COMMUNICATION FOR DYNAMIC TASK ALLOCATION		5. TYPE OF REPORT & PERIOD COVERED 9 Technical Report.
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) 10 Joel S. Greenstein Mark E. Revesman		8. CONTRACT OR GRANT NUMBER(s) 15 N00014-81-K-0143
9. PERFORMING ORGANIZATION NAME AND ADDRESS Industrial Engineering & Operations Research Virginia Polytechnic Institute & State University Blacksburg, VA 24061		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS SRO-101 12 31
11. CONTROLLING OFFICE NAME AND ADDRESS Office of Naval Research, Code 455 800 North Quincy Street Arlington, VA 22217		12. REPORT DATE Aug[redacted]81 13. NUMBER OF PAGES 37
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

human-computer systems, human-computer interaction, human-computer interface, human-computer dialog, human-computer communication, human-computer task allocation, modeling, decision making, simulation

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This paper investigates human-computer communication in multitask decision making situations. It is proposed that tasks in these systems be allocated in a dynamic manner. Communication between human and computer is essential for dynamic allocation to enhance system performance. Simulation experiments investigate two modes of communication: implicit, in which the human's planned actions are relayed to the computer by the use of model of the human's decision strategy, and explicit, in which the human overtly describes his decisions to the computer. Results indicate that implicit communication can significantly

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20. ABSTRACT

enhance system performance if the computer uses a method of decision making which complements that of the human. Explicit communication can greatly enhance system performance, but there is an inherent cost in the time it takes the human to transmit his decisions to the computer. It is concluded that the costs of both methods can be traded off so that either implicit or explicit communication may be useful in different situations. Further research is suggested for defining complementary strategies using human models and for investigating trade-offs between implicit and explicit communication.

ACKNOWLEDGEMENTS

This research was supported by the Office of Naval Research under ONR Contract Number N00014-81-K-0143, and Work Unit Number SRO-101. The effort was supported by the Engineering Psychology Programs, Office of Naval Research, under the technical direction of Dr. John J. O'Hare. A version of this report will appear in the Proceedings of the 1981 IEEE International Conference on Cybernetics and Society, Atlanta, Georgia, October, 1981.

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INTRODUCTION

Increased automation of human-machine systems requires the human to supervise and make decisions about the operation of many parallel subsystems. The human is also beginning to interact with computers having responsibilities much the same as those of the human: the supervision of ongoing tasks and decision making with respect to these tasks. With human and computer both acting as decisionmakers, the allocation of tasks to human and computer becomes a basic issue of system design.

This work is influenced by the belief that in the operation of multitask dynamic systems, there exists a subset of tasks which might best be allocated to human or computer in a dynamic or situation dependent manner. This approach to human-computer task allocation contrasts with the static approach suggested, for example, by Licklider (1960) in which a set of tasks is partitioned into two subsets -- one being allocated to the human, the other to the computer. A dynamic approach allocates a particular task to the decisionmaker (human or computer) that has at that moment the resources available for performing the task. Rouse (1977; 1981) suggests that a dynamic approach to task allocation has several advantages with respect to the static approach, including improved utilization of the system's resources, less variability of the human's workload, and the

possibility for the human to have an improved knowledge of the overall system state. Further, this sharing of task responsibility lessens the risk involved in either decisionmaker's diversion of attention to one task and results in a system more tolerant of failure in either decisionmaker. But the overlapping of reponsibilities also introduces the possibility that conflicts between and redundant actions by the two decisionmakers will occur.

The problem of conflict between decisionmakers might be approached as a problem of supplying each decisionmaker with information regarding the present and planned actions of the other decisionmaker. In particular, the problem of supplying the computer with information regarding the action plan of the human appears to be critical, because it is this information flow that permits a situation in which the computer actively seeks to accomodate the human. This enables the human to retain the initiative and primacy associated with a supervisory role. The computer serves as a decision aid, adapting its task performance to complement that of the human.

The simulation study presented in this paper investigates implicit and explicit means of human-computer communication to facilitate dynamic task allocation in multitask, time-constrained environments. The distinction between implicit and explicit communication is based upon

whether or not the human and the computer engage in a dialogue to determine the appropriate allocation strategy. Models of human attention allocation might be used to communicate implicitly to the computer the human's planned actions (Greenstein, 1980). This approach to dynamic task allocation might be particularly appropriate in multitask, time-constrained environments. Implementation of such an approach requires the development and appropriate use of predictive models of human attention allocation performance. Alternatively, the human might explicitly communicate planned actions to the computer. It would then be necessary to define and optimize the human-computer dialogue required to achieve dynamic task allocation.

THE MULTITASK SITUATION

Approach

The simulation uses a queueing approach to investigate human-computer interaction in a multitask decision making situation. The situation is that of a human and computer simultaneously scanning a series of ten instruments or displays in order to detect indications of failure in related subsystems. The human or computer repair failed subsystems according to a predetermined strategy based on the order of the instruments rather than the times when the failures occurred. Each time the human or computer finishes repairing a subsystem, all ten instruments are immediately scanned by that entity and decisions as to which subsystem to next repair are made. Since this decision takes into account the states of all subsystems, the scan time is constant and instantaneous for each decision. The time taken to scan all instruments and come to a decision is assumed to be negligible.

Two modes of communication between human and computer are considered. If the human were to explicitly communicate knowledge of his actions to the computer, conflict between the two decisionmakers could perhaps be completely avoided; the computer would not attempt to repair the same subsystem

being repaired by the human. Such explicit communication, however, would quite possibly be costly in terms of time, since the human would have to inform the computer of his actions at all times. This type of communication will be explored briefly in the second of the two experiments presented. An alternative to this mode of communication might be achieved by supplying the computer with a model of how the human selects subsystems for repair. The computer can use this model to make assumptions about which subsystem the human is likely to select; it can then select its own actions so as to avoid conflict. While explicit communication is expected to be nearly perfect, it is likely that implicit communication such as this would not be; when working with humans, it is expected that any model of behavior will be less than perfectly predictive. In the first experiment we investigate the use of less than perfect models to guide a second decisionmaker's action selection.

In the first experiment, investigating implicit communication, it is assumed that the time required to repair a subsystem is constrained by that system and not by the speed of the entity performing the repair. Repair times are exponentially distributed with identical means for both the human and the computer. The effective speeds of the human and computer are therefore identical. In the second experiment, investigating explicit communication, it is

assumed that there is a time cost associated with communicating the human's action plans to the computer. An increment is added to the human's repair time to reflect the time required to carry out this communication. The times between failures are exponentially distributed with the mean varied between conditions, but identical for each subsystem within a condition. The period from the time a subsystem fails to the time it is repaired (down time) is the sum of the time for that subsystem to be selected for repair by an entity (waiting time during repair of other subsystems) plus the time required to repair the subsystem once it has been selected.

For every experimental condition, two trials of the simulation were performed with each trial consisting of 10,000 events (subsystem failures). Each of the two simulations started with a different random seed. In this way, statistical analysis could be performed using the variance between the two runs as error variance.

Variables

In order to describe the simulated system, it is necessary to discuss several variables and parameters which constrain the system. The following list presents these descriptive parameters.

a) Mean time between failures (MTBF) for each subsystem was manipulated experimentally. MTBF was exponentially distributed with means of 25, 50, 75 and 100 seconds. Since the number of subsystems is not infinite (there are ten instruments) and failures are not permitted to queue up in individual subsystems (no new failures can occur in a subsystem while it is in the failed state), it is not critical that the system be stable in queueing terms; an infinite queue cannot form. The only effect of an unstable system will be that some subsystems never get repaired throughout the course of the simulation. Realistically, a MTBF of 25 seconds per subsystem is absurd when it takes 10 seconds to repair a subsystem. In a simulation, however, this value can be used to severely load the decisionmakers, permitting them little or no idle time.

b) The number of instruments was held constant at 10. Varying the value of MTBF, rather than the number of instruments, was chosen as the means of decisionmaker loading so that dependent measures of individual subsystems could be compared directly across all conditions.

c) The mean time to repair a subsystem (MTTR) is the time required to repair a subsystem once service to that subsystem is initiated. In the first experiment, this time was exponentially distributed with a mean of 10 seconds for both the human and computer. As previously mentioned, this speed equality between human and computer is explained in terms of system constraints, rather than an assumption that humans and computers are equally fast.

In the second experiment, it was assumed that the time necessary for the human to inform the computer of subsequent actions was constant each time a decision was made. A constant amount of time was therefore added to the human's repair time in the explicit communication situation. This delay was varied experimentally and took the values 1, 2, 3, 4, and 5 seconds. This delay is the "cost" incurred by explicit communication.

d) The service policy of the human was held constant throughout the experiment. The human scanned the set of 10 instruments and noted those subsystems that required repair. This scan time was assumed to be negligible. The human then repaired the first failed subsystem in the series of subsystems ordered from 1

to 10. Upon completion of this repair, the human initiated a new scan of the instruments. That the human serves earlier subsystems in the series in preference to later subsystems is not meant to imply that earlier subsystems are of greater importance than later ones. It is simply meant to reflect that the human adopts some policy for servicing the subsystems.

Two basic service policies for the computer were investigated in the first experiment. In one policy (termed the identical strategy) it is assumed that the computer uses its model of the human's actions to mimic the human's actions. Thus, the computer follows a service policy identical to the human's policy outlined above. In the second policy (termed the complementary strategy) it is assumed that the computer uses its model of the human's actions to derive a service policy that, in concert with the human's policy, seeks to minimize total down time of the subsystems within the system. In this policy, the computer scanned the set of 10 instruments and noted those that required repair, as described above. The computer then repaired the last failed subsystem in the series of subsystems. Upon completion of this repair, the computer initiated a new scan of the instruments. The premise of this policy is that with

the human attending to the first failed subsystem of subsystems 1,2,...,10 noted in his scan, the computer is least likely to conflict with the human if it chooses the last failed subsystem noted in its scan. Note that conflict is defined to occur when one entity repairs a system that is already being repaired by the other entity. In this study, both entities are permitted to repair this subsystem as if there were no other entity also attempting to carry out the repair. The penalty incurred by conflict, then, is that one entity allocates time to a redundant repair when it might otherwise be repairing an unattended failed subsystem.

e) In the first experiment, the predictive validity of the model used to achieve implicit communication was varied by having the computer follow the identical or complementary strategies in only a certain percentage of the decisions. A less than perfect model for communication of the human's actions was simulated by varying the percentage of decisions that the computer makes which are consistent (in an identical or complementary manner) with the human's actions. The consistent strategy was followed either 0%, 20%, 40%, 60%, 80% or 100% of the time. To simulate a condition in which the actions of the computer bear no

relationship to the human's actions, the remainder of the computer's decisions selected failed subsystems for repair in a random fashion. When the consistent strategy was followed 0% of the time, the computer selected the subsystems to be fixed totally randomly. In this situation, implicit communication was non-existent. At the other extreme, with the 100% consistent strategy (identical or complementary), the computer had a perfect model of the human and implicit communication was maximized.

f) The total down time experienced by each subsystem over a simulation trial was employed as a measure of system performance under the manipulation of the variables listed above.

EXPERIMENTS

Experiment 1

In this simulation experiment, two major issues were of interest. The first concerns the manner in which the computer uses knowledge of the human's actions to select its own actions. If both the identical and complementary computer strategies employed here produce increases in performance over a random action selection scheme, it could be asserted that a computer's strategy referencing a model of the human is preferable to a non-referencing strategy. It is expected, however, that the fact that the computer's strategy is based upon a model of the human does not of itself result in enhanced system performance. The strategy derived from the knowledge of the human's actions must be selected to complement these actions rather than compete with them. Thus, it is expected that only the complementary computer strategy will improve overall system performance over the random computer strategy baseline. In addition, it is expected that the identical and complementary strategies will affect performance of the individual subsystems differently. Using the identical strategy, the first several subsystems will be serviced much more frequently than later subsystems. With the complementary strategy, both the initial and the final few subsystems will be

serviced frequently, while service of the middle subsystems will be less frequent.

The second issue concerns the sensitivity of system performance to the model's predictive validity. It is expected that as the predictive validity of the computer's model of the human decreases, and, as a consequence, the computer's action strategy is less frequently related to the actions of the human, gains in system performance produced by the use of the model will also be offset. There should be a point at which the use of a model with little predictive validity produces performance approximating that of using no model at all. The location of this point is of interest as it serves to indicate how accurate models of the human must be to be of use in a human-computer system.

The first set of experiments investigated the effects of subsystem number, the manner in which the computer employs the model of the human to derive its own service policy, and the predictive validity of the model upon subsystem down time.

Two means by which the computer might employ knowledge of the human's actions to guide its own actions were investigated -- the identical and the complementary strategies discussed earlier. The identical and

complementary strategies affect system performance in significantly different ways. An analysis of variance indicates a highly significant effect of strategy ($F(1,480)=3906.93$, $p<.0001$). The average down time over all subsystems is approximately 22285 seconds per subsystem (27.1% of the time) for the identical strategy, but 19422 seconds per subsystem (23.6% of the time) for the complementary strategy, indicating a 2.5% increase in subsystem operating time for the latter strategy (the total time for the simulations averaged 82200 seconds). Such a difference can be explained by conflicts being more likely to occur when the strategy being followed is identical, particularly with the speeds of the human and computer effectively equal.

A more interesting effect is the interaction between subsystem and strategy (Fig. 1).

For this effect, $F(9,480)=694.77$ ($p<.0001$). Note that for the first several subsystems, the curves appear to be almost identical. Apparently, having two decisionmakers both follow an identical strategy of repairing the first failed subsystem in the series does not significantly decrease the down time of the first several subsystems from that achievable when only one decisionmaker follows this strategy. The major differences in down time occur in the later subsystems. When the computer follows the identical

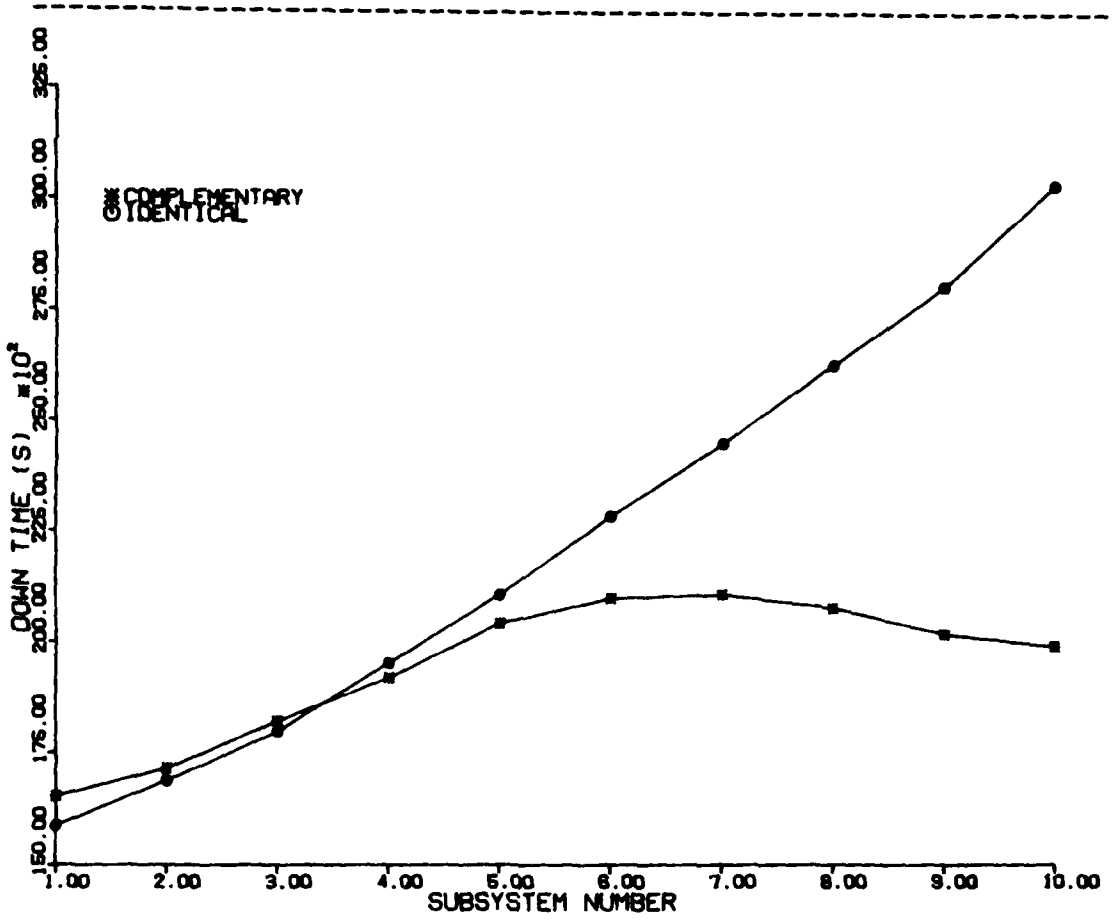

Figure 1. Total down time for each subsystem with the computer following identical and complementary strategies.

strategy, the later subsystems are rarely repaired and greater delays occur on each subsequent subsystem. Using the complementary strategy, however, the delays experienced by the final few subsystems begin to approach those experienced by the initial few. For no subsystems is the identical strategy significantly better then the complementary strategy. Fig. 1 indicates that strategies based on a model of the human are not all equal. This

implies that even if a model of the human is accurate, the strategy that should be employed to optimize the human-computer system is not a function of that model alone. The strategy must also consider whether conflicts are likely to occur, and how to avoid them. While this is not surprising, it does point out that developing a model of the human is not sufficient for design of a task allocation system. Further work would be necessary to determine the proper allocation strategy based on a given model of the human.

In a system employing models to implicitly communicate the human's actions to a computer, it is of interest to know how the degree to which the model successfully predicts human performance affects system performance. To investigate this issue, a perfect model of the human is initially used by the computer in each of the above strategies. This model is then degraded in a manner which effectively permits the computer to base its action selections upon those of the human for only a specified percentage of its decisions. The remaining percentage of its actions are random selections unrelated to the actions of the human. By observing the effects of this degradation, it may be possible to determine how representative a model must be to be useful in improving system performance.

Figure 2 demonstrates the effects of degradation of the human model for both the complementary and identical

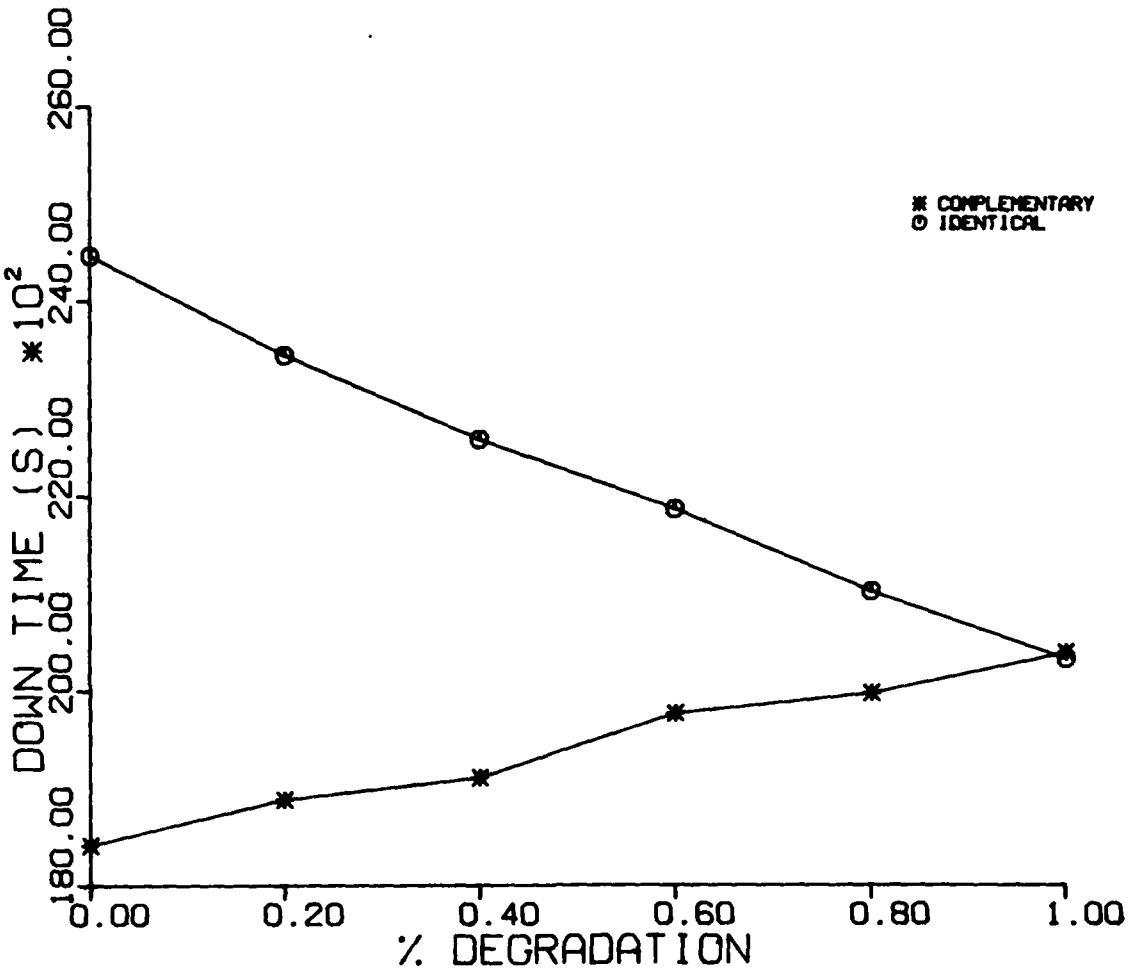

Figure 2. Subsystem down time for different amounts of model degradation with the computer following identical and complementary strategies.

strategies.

Looking at the complementary strategy, it can be seen that as model degradation increases, the down time experienced by the subsystems increases at what appears to

be a constant rate. A Duncan's multiple range test indicates that each level of degradation is significantly different from every other at the .05 level. Thus, while having a perfect model of the human is preferable, even a very poor model (e.g., 20% predictive/80% random in this experiment) can improve system performance significantly.

When the computer uses the identical strategy, the exact opposite effect is seen. Each increase in model degradation significantly decreases the down time experienced by the subsystems (according to a Duncan test). In fact, the use of the identical strategy degrades performance to a greater extent than the use of the complementary strategy improves it (relative to a baseline random strategy resulting from the use of a model with no predictive validity). This again indicates that care must be taken in selecting the means by which the computer makes use of knowledge of the human's actions. However, if the computer's actions are referenced to the human's actions appropriately, system performance may be improved, even if the model is a clearly imperfect representation of the human.

The amount of degradation does not affect all subsystems identically (Figs. 3 and 4).

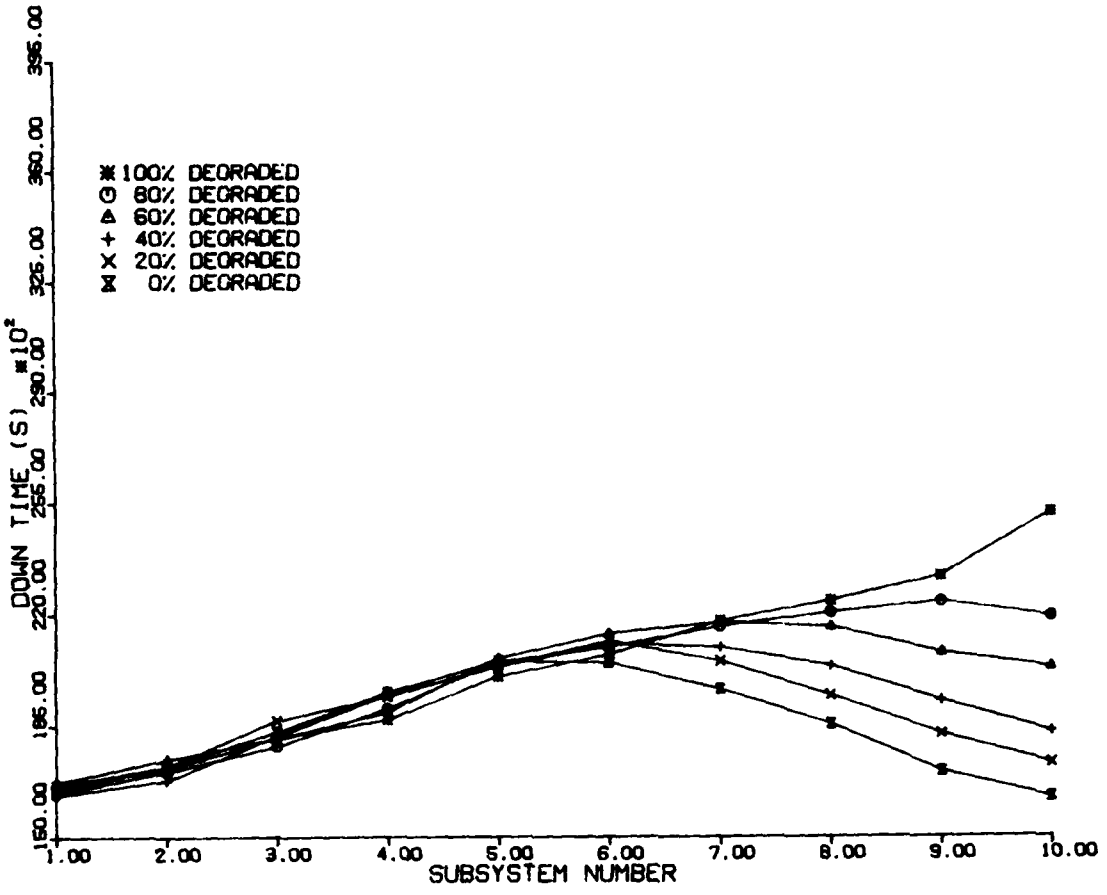

Figure 3. Total down time for each subsystem under different amounts of model degradation for the computer following the complementary strategy.

The strategy X subsystem number X degradation interaction is significant ($F(9,480)=65.84$, $p<.0001$). Figure 3 demonstrates the effects on subsystems of increasing degradation when the computer uses the complementary strategy. The amount of degradation does not appear to significantly affect the total down time on the first five subsystems. As mentioned earlier, it appears that having two decisionmakers work on the same subsystems a

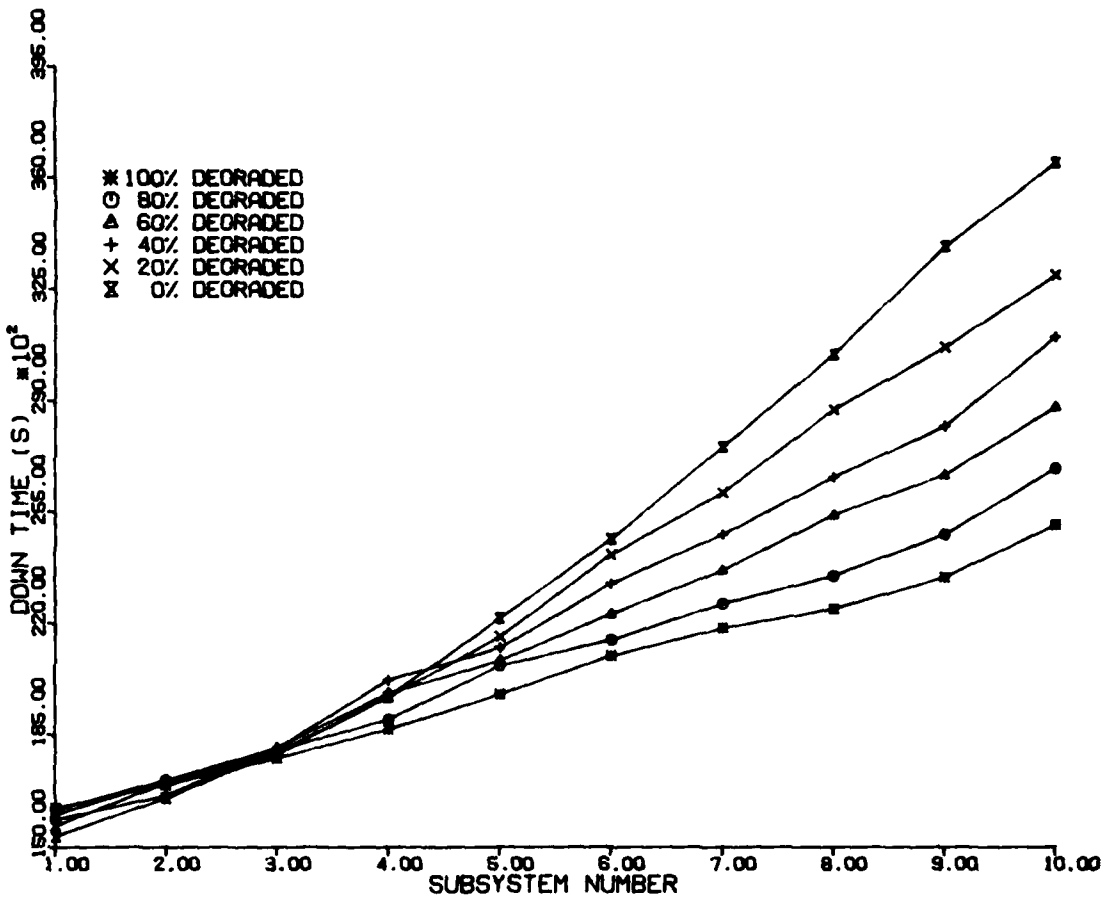

Figure 4. Total down time for each subsystem under different amounts of model degradation for the computer following the identical strategy.

greater percentage of the time (as happens when degradation is increased) does not significantly aid performance. With increased degradation, however, the performance on later subsystems is significantly degraded. It can be seen that this decrement in the later subsystems appears to be linear with percentage of model degradation. This figure indicates that employing a reasonably predictive model of the human in an appropriate manner can not only increase system

performance, but can also decrease the variance among the frequencies with which different subsystems are serviced. This would be desirable in situations in which all subsystems are equally important to the system.

The identical strategy, on the other hand, provides opposite results. As model degradation is increased, system performance improves, especially in the later subsystems. The variance with which subsystems are serviced decreases as well. This reinforces the caveat concerning the manner in which the computer uses knowledge of the human's actions.

Experiment 2

A second experiment was run to investigate the trade-offs between explicit and implicit communication in human-computer multitask situations. With explicit communication it is assumed that the computer is always aware of what the human is doing and that, as a result, conflicts cease to exist. Perfect communication is achieved, however, with the expense of some of the human's time toward communication to the computer upon each of his decisions. With implicit communication (via a model of the human), there is an implicit cost based on lack of ability to perfectly predict the human's performance. In the design of a human-computer system it would be of interest to identify those situations

in which one of these modes of communication is preferable to the other.

In this experiment, the cost of explicit communication was varied from 1 to 5 seconds. As seen in Fig. 5, as cost

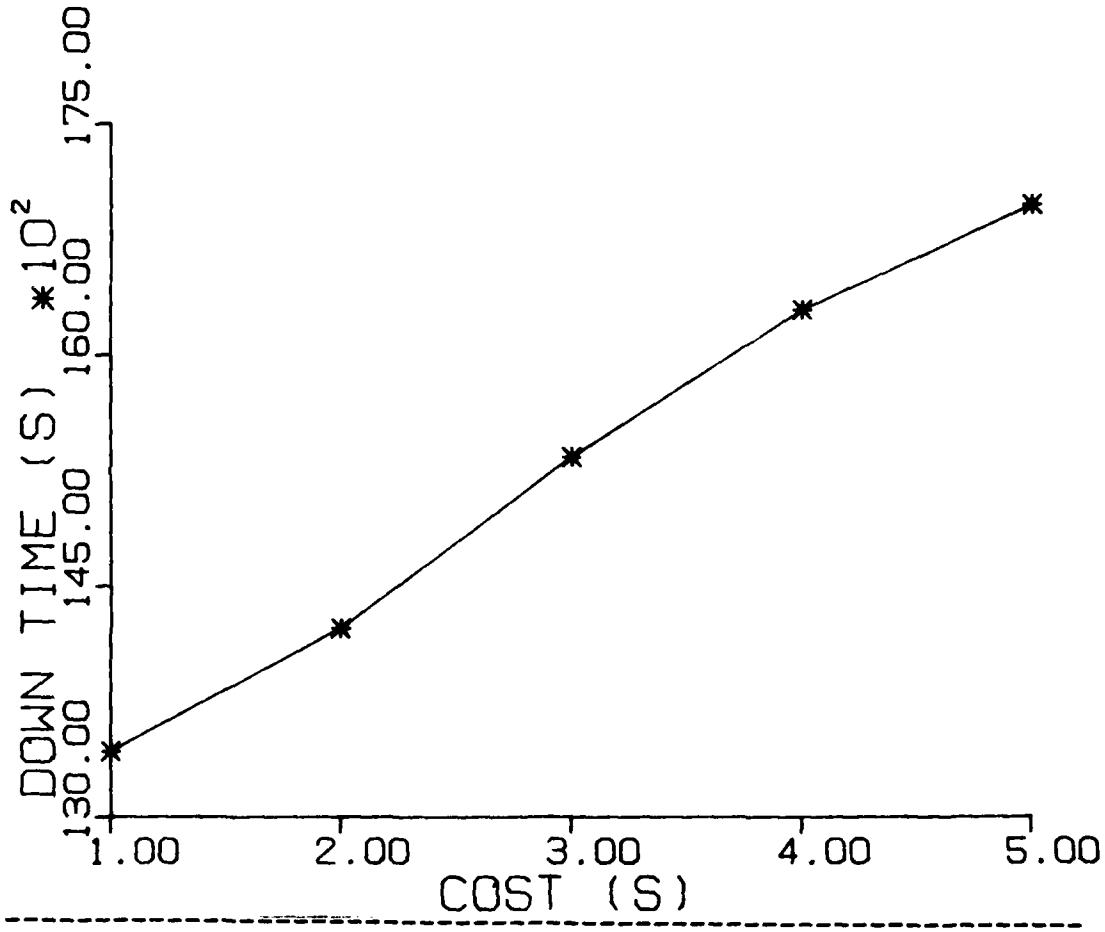

Figure 5. Total down time for different costs of explicit communication.

increases, so does down time ($F(4,100)=303.47$, $p<.0001$).

Since a constant increment is added to the repair time characteristic of the human, the linear increase is as

expected. The interaction between subsystem number and cost is not significant: $F(36,100)=1.233$, $p>.05$. Fig. 6 plots the total down time of each instrument for the different costs of explicit communication tested. Because conflict is not a problem under explicit communication, the complementary strategy employed in the first experiment offers no general advantage over a random strategy. Therefore, the curves in Fig. 6 represent an average over the levels of degradation (or in this situation, randomness) of the complementary strategy investigated in the first experiment.

Comparing figures 3 and 6 yields the interaction of interest. In general, explicit communication achieves better system performance than implicit communication for the parameter values investigated. As the cost of communication increases, however, there appears to be a point at which the implicit communication mode becomes viable. At the largest cost of 5 seconds, explicit communication appears to be no better than implicit communication. Any cost greater then 5 seconds would cause explicit communication to be poorer than implicit communication, even with a poor model of the human. This indicates that the time penalties incurred in requiring explicit communication by the human can perhaps offset the performance decrement to be expected for implicit communication via a less than perfect model. If the time

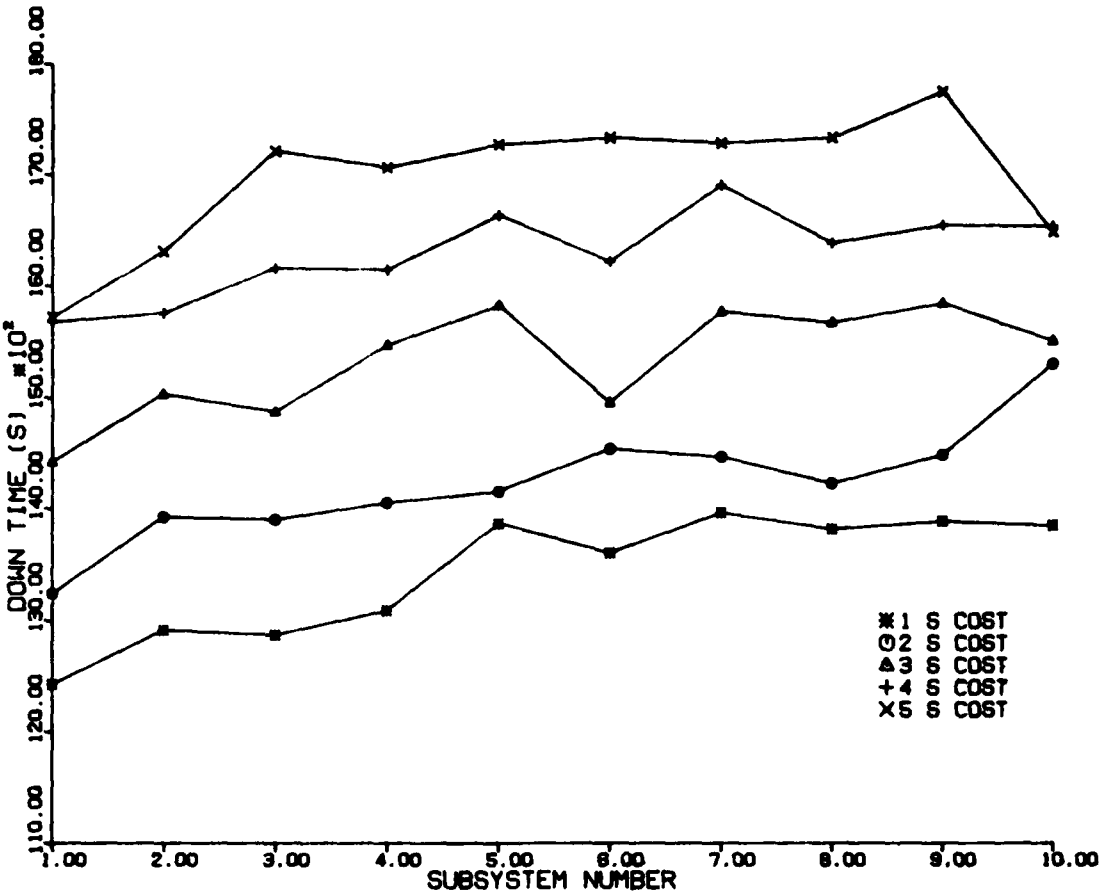

Figure 6. Total down time for each instrument for different costs of explicit communication.

penalties and degree of predictive validity can be quantified for a given application it would be possible for the system designer to determine the most efficient communication mode for a specific application.

CONCLUSIONS

In order to design efficient human-computer multitask systems in which tasks are dynamically allocated to human and computer, communication between the two decisionmakers is critical. Communication of the human's action plans can be achieved by explicit or implicit means. Correct use of these modes of communication and of the information communicated should lead to an improvement in overall system performance.

Several conclusions can be drawn from the first experiment presented. In a human-computer multitask decision making situation, the use of a model to implicitly convey knowledge of the human's actions can significantly aid performance, even when the model is imperfect. This increase in performance is likely to occur because of less conflict and redundancy in decisions; the computer will be better able to select its own actions so as to complement the actions of the human. Availability of a model of the human is not sufficient for successful implementation of such a system, however. Before increased performance can be realized, an appropriate algorithm for employment of the model must be developed. A poor choice of algorithm can lead to poorer performance than that obtained with no model at all. When a human-computer system employing implicit

communication is designed, two points of information must be of interest: the selection of an appropriate model of the human and the determination of the manner in which the computer acts on this model to complement human performance.

The second experiment indicates that when choosing to employ explicit or implicit communication within a human-computer system, the costs associated with each must be traded against one another. There are likely to be situations in which employment of one or the other mode is advantageous. Further research is necessary in defining this trade-off and in the evaluation of the costs inherent in each mode of communication. Such research should lead to usable criteria for design decisions regarding human-computer interaction in multitask situations.

This work demonstrates the need for the development of models of the human decisionmaker as a function of system parameters, as well as the need to develop algorithms which describe how to effectively use such models. This work also demonstrates the need to define appropriate dialogue styles for systems employing explicit communication between human and computer decisionmakers in multitask, time-constrained situations. Research in these areas will provide means to increase human-computer system performance and to incorporate computers within these systems in a manner more compatible with the human's capabilities.

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Commanding Officer
ONR Eastern/Central Regional Office
ATTN: Dr. J. Lester
Building 114, Section D
666 Summer Street
Boston, MA 02210

Commanding Officer
ONR Branch Office
ATTN: Dr. C. Davis
536 South Clark Street
Chicago, IL 60605

Commanding Officer
ONR Western Regional Office
ATTN: Dr. E. Gloye
1030 East Green Street
Pasadena, CA 91106

Office of Naval Research
Scientific Liaison Group
American Embassy, Room A-407
APO San Francisco, CA 96503

Director
Naval Research Laboratory
Technical Information Division
Code 2627
Washington, D.C. 20375 (6 cys)

Mr. Thomas McAndrew
Code 32
Naval Undersea Systems Center
New London, CT 06320

Dr. Robert G. Smith
Office of the Chief of Naval
Operations, OP987H
Personnel Logistics Plans
Washington, D.C. 20350

Dr. Jerry C. Lamb
Combat Control Systems
Naval Underwater Systems Center
Newport, RI 02840

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Human Factors Department
Code N215
Naval Training Equipment Center
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Training Analysis and Evaluation Group
Naval Training Equipment Center
Code N-OOT
Orlando, FL 32813

Mr. Louis Chmura
Code 7503
Naval Research Laboratory
Washington, DC 20375

CAPT Darrell D. Dempster, SC, USN
PMA 270
Naval Air Systems Command
Washington, DC 20361

Dr. Albert Colella
Combat Control Systems
Naval Underwater Systems Center
Newport, RI 02840

Dr. Gary Poock
Operations Research Department
Naval Postgraduate School
Monterey, CA 93940

Dean of Research Administration
Naval Postgraduate School
Monterey, CA 93940

Mr. Warren Lewis
Human Engineering Branch
Code 8231
Naval Ocean Systems Center

Dr. Robert French
Naval Ocean Systems Center
San Diego, CA 92152

Department of the Navy

Dr. Ross L. Pepper
Naval Ocean Systems Center
Hawaii Laboratory
P.O. Box 997
Kailua, HI 96734

Dr. A. L. Slafkosky
Scientific Advisor
Commandant of the Marine Corps
Code RD-1
Washington, D.C. 20380

Dr. Mel C. Moy
Code 302
Naval Personnel R&D Center
San Diego, CA 92152

Commanding Officer
MCTSSA
Marine Corps Base
Camp Pendleton, CA 92055

Chief, C^3 Division
Development Center
MCDEC
Quantico, VA 22134

Mr. Arnold Rubinstein
Naval Material Command
NAVMAT 0722 - Rm. 508
800 North Quincy Street
Arlington, VA 22217

Commander
Naval Air Systems Command
Human Factors Programs
NAVAIR 340F
Washington, D.C. 20361

Commander
Naval Air Systems Command
Crew Station Design,
NAVAIR 5313
Washington, D.C. 20361

Mr. Phillip Andrews
Naval Sea Systems Command
NAVSEA 0341
Washington, D.C. 20362

Department of the Navy

Commander
Naval Electronics Systems Command
Human Factors Engineering Branch
Code 4701
Washington, D.C. 20360

Dr. Ramon Hershman
Code 302
Naval Personnel R&D Center
San Diego, CA 92152

Dr. Thomas Fitzgerald
Code 101
Newport Laboratory
Naval Underwater Systems Center
Newport, RI 02840

CDR Robert Biersner
Naval Medical R&D Command
Code 44
Naval Medical Center
Bethesda, MD 20014

Dr. Arthur Bachrach
Behavioral Sciences Department
Naval Medical Research Institute
Bethesda, MD 20014

Dr. George Moeller
Human Factors Engineering Branch
Submarine Medical Research Lab
Naval Submarine Base
Groton, CT 06340

Dr. James McGrath, Code 302
Navy Personnel Research and
Development Center
San Diego, CA 92152

LCDR Stephen Harris, USN
Human Factors Engineering Division
Naval Air Development Center
Warminster, PA 18974

Dr. Richard Neetz
Code 1226
Pacific Missile Test Center
Pt. Mugu, CA 93042

Department of the Navy

Navy Personnel Research and
Development Center
Planning & Appraisal
Code 04
San Diego, CA 92152

Navy Personnel Research and
Development Center
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San Diego, CA 92152

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Development Center
Performance Measurement &
Enhancement
Code 309
San Diego, CA 92152

Dr. Julie Hopson
Human Factors Engineering Division
Naval Air Development Center
Warminster, PA 18974

Mr. Jeffrey Grossman
Human Factors Branch
Code 3152
Naval Weapons Center
China Lake, CA 93555

Human Factors Engineering Branch
Code 1226
Pacific Missile Test Center
Point Mugu, CA 93042

Mr. J. Williams
Department of Environmental
Sciences
U.S. Naval Academy
Annapolis, MD 21402

Dean of the Academic Departments
U.S. Naval Academy
Annapolis, MD 21402

Mr. John Impagliazzo
Code 101
Newport Laboratory
Naval Underwater Systems Center
Newport, RI 02840

Department of the Navy

Walter Warner, Code KOZ
Strategic Systems Department
Naval Surface Weapons Center
Dalgren, VA 22448

Human Factors Section
Systems Engineering Test
Directorate
U.S. Naval Air Test Center
Patuxent River, MD 20670

Human Factor Engineering Branch
Naval Ship Research and Development
Center, Annapolis Division
Annapolis, MD 21402

CDR W. Moroney
Code 55MP
Naval Postgraduate School
Monterey, CA 93940

Mr. Merlin Malehorn
Office of the Chief of Naval
Operations (OP-115)
Washington, D.C. 20350

Department of the Army

Mr. J. Barber
HQS, Department of the Army
DAPE-MBR
Washington, D.C. 20310

Dr. Joseph Zeidner
Technical Director
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Director, Organizations and
Systems Research Laboratory
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Technical Director
U.S. Army Human Engineering Labs
Aberdeen Proving Ground, MD 21005

ARI Field Unit-USAREUR
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C/O ODCSPER
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APO New York 09403

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Life Sciences Directorate, NL
Bolling Air Force Base
Washington, D.C. 20332

Chief, Systems Engineering Branch
Human Engineering Division
USAF AMRL/HES
Wright-Patterson AFB, OH 45433

Air University Library
Maxwell Air Force Base, AL 36112

Dr. Earl Alluisi
Chief Scientist
AFHRL/CCN
Brooks AFB, TX 78235

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The Charles Myers Library
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Stratford
London E15 2LJ
ENGLAND

Professor Dr. Carl Graf Hoyos
Institute for Psychology
Technical University
8000 Munich
Arcisstr 21
FEDERAL REPUBLIC OF GERMANY

Professor B. Shackel
Department of Human Sciences
University of Technology
Loughborough, Leics. LE11 3TU
ENGLAND

Dr. Kenneth Gardner
Applied Psychology Unit
Admiralty Marine Technology
Establishment
Teddington, Middlesex TW11 OLN
ENGLAND

Director, Human Factors Wing
Defence & Civil Institute of
Environmental Medicine
Post Office Box 2000
Downsview, Ontario M3M 3B9
CANADA

Foreign Addressees

Dr. A. D. Baddeley
Director, Applied Psychology Unit
Medical Research Council
15 Chaucer Road
Cambridge, CB2 2EF
ENGLAND

Other Government Agencies

Defense Technical Information Center
Cameron Station, Bldg. 5
Alexandria, VA 22314 (12 cys)

Dr. Craig Fields
Director, Cybernetics Technology Office
Defense Advanced Research Projects Agency
1400 Wilson Blvd
Arlington, VA 22209

Dr. Lloyd Hitchcock
Federal Aviation Administration
ACT 200
Atlantic City Airport, NJ 08405

Dr. M. Montemerlo
Human Factors & Simulation Technology, RTE-6
NASA HQS
Washington, D.C. 20546

Other Organizations

Dr. Jesse Orlansky
Institute for Defense Analyses
400 Army-Navy Drive
Arlington, VA 22202

Dr. T. B. Sheridan
Department of Mechanical Engineering
Massachusetts Institute of Technology
Cambridge, MA 02139

Dr. Arthur I. Siegel
Applied Psychological Services, Inc.
404 East Lancaster Street
Wayne, PA 19087

Other Organizations

Dr. Robert T. Hennessy
NAS - National Research Council
JH #819
2101 Constitution Ave., N.W.
Washington, DC 20418

Mr. John Hemingway
Man-Vehicle Systems Research
MS #239-21
NASA Ames Research Center
Moffett Field, CA 94035

Dr. M. G. Samet
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

Dr. Elizabeth Kruesi
General Electric Company
Information Systems Programs
1755 Jefferson Davis Highway
Arlington, VA 22202

Journal Supplement Abstract Service
American Psychological Association
1200 17th Street, N.W.
Washington, D.C. 20036 (3 cys)

Mr. Edward M. Connelly
Performance Measurement Associates, Inc.
410 Pine Street, S.E.
Suite 300
Vienna, VA 22180

Dr. Richard W. Pew
Information Sciences Division
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02138

Dr. Douglas Towne
University of Southern California
Behavioral Technology Laboratory
3716 S. Hope Street
Los Angeles, CA 90007

Dr. A. K. Bejczy
Jet Propulsion Laboratory
California Institute of Technology
Pasadena, CA 91125